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AN EDAS METHOD-BASED CLUSTERING STUDY TO ASSESS THE LOGISTICS PERFORMANCES OF SELECTED COUNTRIES[1]

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ABSTRACT

The importance of environmentally friendly logistics activities is increasing day by day due to the intensifying globalization and increasing trade volumes of countries. Undoubtedly, the logistics industry contributes positively to national economies; however, this increasing contribution brings environmental concerns. The total amount of CO_2 emissions caused by transportation varies depending on the countries' efforts on green strategies. In this case, it is thought that clustering countries based on their logistics performance indices and CO_2 emissions from transportation may contribute to the sustainable development goals of actors that play an active role in global trade movements. This research study investigates Turkey's position in global trade logistics relative to its competitors, taking into account the Logistics Performance Index (LPI) and the total CO_2 emission values from transportation. For this purpose, the hierarchical K-means clustering analysis was conducted using the six criteria of the LPI published by the World Bank in 2018 and the CO_2 transport-related emission values of 44 countries. The R programming language was used for clustering analysis. According to the analysis results of the study, 44 countries were divided into 4 clusters in terms of their logistics performance and CO_2 emissions sourced by transportation. In addition, performance evaluations of clustered countries were carried out with the EDAS method, which is one of the Multi-Criteria Decision Making (MCDM) methods on each cluster basis. According to the results obtained from the EDAS method, the countries within each cluster are ranked from the best to the worst. This study can provide a practical framework for countries to improve their logistics performance with low carbon footprint applications.

Keywords: *Logistic Performance Index, CO_2 Emission, Hierarchical K-means, EDAS Method.*

1. INTRODUCTION

The global supply chain is so complex and multi-layered that maintaining logistics efficiency in such a challenging environment is vital thus; high levels of logistics efficiency represent good management of government services, transport investments, and policies. Concentrations of greenhouse gases (GHG) sourced by certain sectors have been increasing continuously in recent years. Mainly, transportation sectors have a large impact on climate change due to their high greenhouse gas emissions (Miklautsch & Woschank, 2022). The transportation sector makes an undesirable contribution to global greenhouse gas emissions standing out at 16.2% (Ritchie, Roser, & Rosado, 2020). As stated in the Paris Climate Agreement, where 196 countries around the world come together on a common ground perspective, several improvements need to be made in the transportation sector in order to reduce energy consumption and CO_2 emissions.

In order to minimize CO_2 emissions in logistics activities, especially in transportation, which is one of the key elements of international trade, it is necessary to maximize the efficiency of logistics performance. This ensures that CO_2 emissions from logistics activities are reduced to acceptable levels (Polat, Kara & Yalcin, 2022). In the studies that contribute some suggestions to the climate change problem, essential points about the CO_2 emissions from transportation are taken into consideration. With the determination of the CO_2 efficiency level, it is foreseen that the implementation of strong logistics and

[1] This study is an extended version of the abstract titled "Performance Evaluation through Clustering Analysis based on Logistics Performance Index and Transport Emissions: An Empirical Analysis" presented at the 10th EJSER symposium.

transportation strategies will positively contribute to preventing global climate change in the countries.

Generally, it is emphasized that there is causality in the CO_2 emissions in the Gross Domestic Product, foreign trade volumes, and logistics movements of the countries. It is seen that especially developed and developing countries are negative pioneers in CO_2 emissions (Antoni et al., 2015; Guo et al., 2016; Li et al., 2019; Jiang et al., 2020; Yang et al., 2019; Polat et al. 2022). Because of successful and effective steps that countries will take to improve their logistics performance, greater improvements will be experienced in this field, and they will contribute to sustainability as a result of their environmentalist approach. Due to this butterfly effect, a global healing movement will be triggered.

This study aims to cluster countries by using the LPI values and the CO_2 emissions from transportation. Following that, the performances of the clustered countries are ranked from best to worst for each cluster on each cluster basis. This study differs from the previous literature in some aspects. First, clustering analysis was performed based on transport–related CO_2 emission and LPI values, which have been understudied thus far. Second, the Hierarchical K-Means algorithm was used for clustering analysis, and the analysis was conducted using R language. Following this, each clustered country's performance was evaluated using the EDAS method within the cluster which they divided into.

This study contributes to the literature by clustering the countries according to the Transport CO_2 emission and LPI. In this research paper, the Hierarchical K-means algorithm was conducted for clustering, and the EDAS, one of the MCDM methods, was used for ranking analysis. The hierarchical K-means clustering analysis was performed by using R Software. The LPI and transport-related CO_2 emissions data (2018) of 44 countries were selected to perform the clustering analysis. The countries of each cluster from highest to lowest performance were ranked by using the EDAS method. The aim here is to compare the results of the EDAS method with the results of the clustering analysis so that the performance ranking of each country can be evaluated more effectively. Creating separate rankings for each cluster can help countries to assess their logistics performance more efficiently.

The paper is structured as follows: In the second section, the literature review of clustering analysis and MCDM on LPI is given. In the third section, data and methodology of the study are described. Subsequent section provides the findings of the empirical analyses. Finally, theoretical and methodological implications of the study are discussed in the conclusion section.

2. BACKGROUND

There is an important number of studies about the clustering of LPI in the literature. Popal et al. (2010) examined the logistics performances of countries by using the clustering analysis. It has been emphasized that Dynamic Clustering Analysis was useful in clustering countries. Danacı and Nacar (2017) carried out a comparative analysis with EU member countries by considering the logistics performance of Turkey's foreign trade activities in their research. The data used in the study are 2014 logistics performance indexes (LPI) and import/export values of EU 28 countries and Turkey, which is nominated for membership. The findings of the hierarchical clustering analysis depict the Turkey's position in foreign trade and the EU member states with which it has close relations were revealed.

Bayır and Yılmaz (2017) evaluated the importance of LPI sub-criteria. The authors found timeliness of the most crucial criterion. Roy et al. (2018) performed the clustering analysis with LPI and per capita GDP variables. In the research, the K-means algorithm was used for the clustering analysis, and multivariate adaptive regression spline (MARS) was used to find out the complex non-linear relationship between the variables. In the research, the authors clustered 129 countries. The dataset was formed based on per Capita GDP and Overall LPI Score. Upon the clustering analysis result of the 129 countries, five clusters were obtained. Rezaei et al. (2018) addressed the weights of six components used in LPI and infrastructure has been determined as the most important criterion.

Kısa and Ayçin (2019) revealed the importance of the weights of LPI's sub-criteria. The authors determined the most essential criteria as logistics service quality, infrastructure, and international shipment, respectively. According to the analysis result, Germany, the Netherlands, and Sweden were ranked as first, second, and third, respectively. Yıldız et al. (2020) determined the current situation of Turkey's position as 34th out of 90 countries by conducting a hierarchical clustering analysis. Işık et al. (2020) compared the importance weights of LPI's sub-criteria. The authors identified the most essential criterion as timeliness. According to the analysis results, the Czech Republic, Poland, and Hungary were ranked first, second, and third, respectively. Eren & Ömürbek (2021) clustered the logistic performances of OECD countries and Turkey. Polat et al. (2022) clustered the logistic performances of the same countries.

Table 1 lists studies that specifically evaluated LPI using MCDM and clustering methods. As seen in Table 1, the existing studies in the literature mainly focused on OECD countries, European Union countries, and G20 countries.

Table 1. Summary of the Existing Studies on Clustering Analysis and MCDM Methods in Logistics

Study	Variables	Methods	Findings
Popal et al. (2010)	Logistic Performance Index (LPI) data between 2007 and 2010	Dynamic Clustering Analysis	The positions and group members of Romania was detected.
Trappey et al. (2010)	Service needs, preferences, and outsourcing of 98 auto and auto part manufacturers	Ward clustering method and K-means algorithm	Distribution and distribution services have the highest percentage of outsourcing services.
Danacı & Nacar (2017)	2014 Logistics Performance Indexes (LPI) and import/export data of 28 EU countries	Hierarchical clustering analysis	The positions and group members of Turkey and other countries in foreign trade have been determined.
Bayır & Yılmaz (2017)	2014 Sub-criterias of Logistics Performance Indexes (LPI) of 20 European countries.	Analytical Hierarchy Process (AHP) and VIKOR	The importance of criteria's were found and the countries were ranked.
Roy et al. (2018)	2014 Logistics Performance Indexes (LPI), Gross Domestic Product (per capita)	Clustering by K-means data mining algorithm and multivariate adaptive regression spline (MARS)	The clusters of countries were obtained.
Rezaei et al. (2018)	Sub-criterias of Logistics Performance Indexes (LPI) of 107 countries	BWM	The importance levels of the criteria have been determined.
Kısa and Ayçin (2019)	Sub-criterias of Logistics Performance Indexes (LPI) data between 2012 and 2018 of OECD countries	SWARA, EDAS	The importance levels of the criteria have been determined and the countries were ranked.
Yıldız et al. (2020)	Logistics Performance Index (LPI) data from 2012 to 2018 of 90 countries.	Hierarchical clustering analysis. SPSS 22 statistical program was used.	The positions and group members of countries have been determined. Turkey was ranked 34th.
Işık et al. (2020)	Sub-criteria of Logistics Performance Index (LPI) of 11 European countries	SV, MABAC	The importance levels of the criteria have been determined and the countries were ranked.

Eren & Ömürbek (2021)	Logistic Performance Index (LPI) of OECD Countries	Canopy algorithm was applied by using Weka program.	Countries were divided into four clusters.
Polat et al. (2022)	Logistic Performance Index (LPI), CO_2 emissions per capita, CO_2 emissions efficiency per capita of 150 countries	Hierarchical & non-Hierarchical Clustering Analysis	Different clustering results were obtained from each method.

3. METHODOLOGY

The efficiency of the transportation systems of the countries and the profitability of foreign trade and industry are closely related. The sustainability of logistical agility and efficiency levels in operations is linked to transport infrastructure (Senir, 2021). Improving transport infrastructure has a significant impact on the productivity and cost structure of businesses (Haughwout 2001; Ojala & Çelebi, 2015). The Logistics Performance Index (LPI), which is released by the World Bank in every two years since 2007, is a global benchmarking tool created to help countries identify the challenges and opportunities of trade and transport. The latest LPI, which was provided by World Bank in 2018, covers 160 countries. The LPI matrix allows the countries to perform a comparative perspective on their logistics performance (Alyoubi, 2021). In addition, the countries use the LPI to improve their logistic performance and strategic movement skills in their supply chain process.

These countries participating in the LPI survey provide quantitative feedback on how easy or difficult it is to transport common goods. The six leading indicators of LPI combined the performance-related evaluations of logistics actors who have an active role in international trade on a five-point scale. Thereby, LPI helps policymakers, foreign trade companies, and national administrators to eliminate or reduce the barriers encountered in global trade and serves as a roadmap to develop transportation services.

The six dimensions below represent the main points of the logistics industry. These six dimensions that represent the logistics performance of countries are as follows, respectively:

Customs: It is an indicator of efficiency and productivity in the customs clearance process while performing foreign trade transactions of countries.

Infrastructure: It is an indicator of the quality and efficiency of countries' transport and trade infrastructures.

International Shipments: It is an indicator of the ease of shipping at competitive prices.

Logistics Competence: Efficiency, and quality of logistics services.

Tracking and Tracing: It is the ability to track the shipments in the most effective way.

Timeliness: It is the rate of delivery of the shipments to the recipient at the desired time as planned (Arvis, et al., 2018).

The other variable of this research is CO_2 emissions from transport (Tonnes of CO_2 equivalent, Thousands). The road transport mode covers almost three-quarters of the CO_2 emissions from transport (Yang et al., 2015). While economic sanctions related to energy consumption are effective on fuel consumption, it is still late to take environmentalist steps in the ongoing global goods transportation (Schipper, 2009). Insistent steps on climate change, which are especially suppressed by global dynamics, will result in favor of countries. In order to minimize the amount of transport-related CO_2 emissions, which is one of the most important indicators of sustainable transportation, it is thought that it can be beneficial for countries to see their current position through this research study, which includes this variable.

The purpose of this study is to cluster 44 countries in terms of logistics performance and Transport CO_2

emission values and rank the grouped countries in each cluster in terms of performance weights. For this purpose, the logistics performances of the countries are assessed according to the six criteria in the World Bank's LPI report, and the Transport CO_2 emission values are evaluated according to the Transport CO_2 emission values published by the Organization for Economic Co-operation and Development (OECD) database. Briefly, the dataset was obtained from the World Bank and the OECD database. Clustering analysis was performed with the R program. In this paper, the Hierarchical K-means algorithm was used for clustering the countries in terms of logistic performance. For evaluating the performance rankings of the countries the EDAS calculation steps were applied.

The limitations and constraints of the study were mainly experienced with the data set. The World Bank shared the latest calculated LPI values in 2018. Although the shared matrix include 160 countries, only 44 of them had relevant Transport CO_2 emissions data. Hence, the study covered only 44 countries, having 2018 Transport CO_2 emissions data which was shared by the OECD database. The data matrix was presented in Table 2.

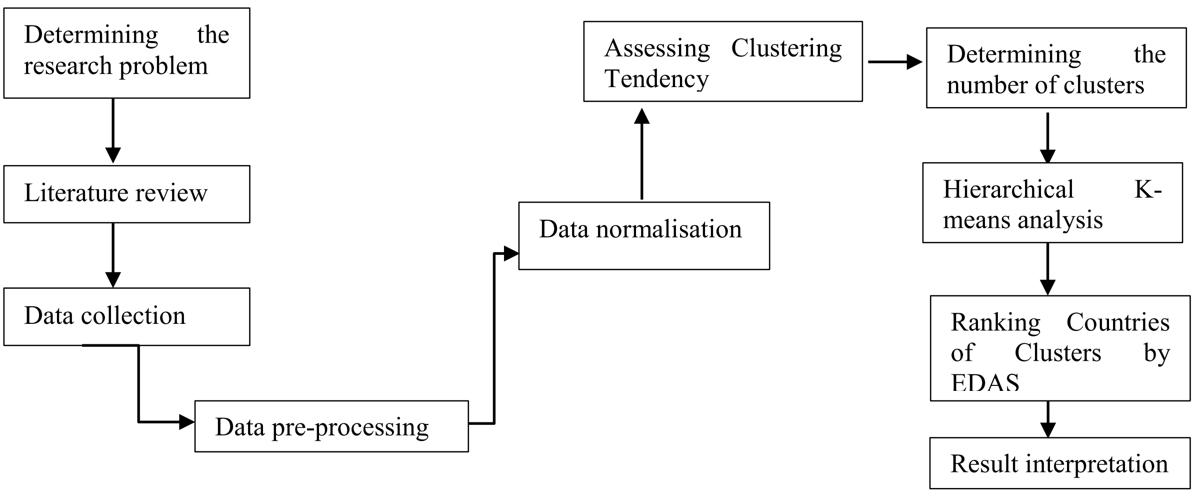
Table 2. Data Matrix

Country	Greenhouse Gases by transport sources (Tones of CO_2 equivalent, Thousands)	Customs	Infrastructure	International	Quality	Tracking	Timeliness
Australia	100262.00	3.87	3.97	3.25	3.71	3.82	3.98
Austria	24453.34	3.71	4.18	3.88	4.08	4.09	4.25
Belarus	4040.27	2.35	2.44	2.31	2.64	2.54	3.18
Belgium	26214.52	3.66	3.98	3.99	4.13	4.05	4.41
Bulgaria	9757.69	2.94	2.76	3.23	2.88	3.02	3.31
Canada	184832.06	3.60	3.75	3.38	3.90	3.81	3.96
Chile	28614.67	3.27	3.21	3.27	3.13	3.20	3.80
Croatia	6410.25	2.98	3.01	2.93	3.10	3.01	3.59
Cyprus	2107.37	3.05	2.89	3.15	3.00	3.15	3.62
Czech Republic	18897.68	3.29	3.46	3.75	3.72	3.70	4.13
Denmark	13705.30	3.92	3.96	3.53	4.01	4.18	4.41
Estonia	2468.41	3.32	3.10	3.26	3.15	3.21	3.80
Finland	11658.34	3.82	4.00	3.56	3.89	4.32	4.28
France	132929.12	3.59	4.00	3.55	3.84	4.00	4.15
Germany	163639.45	4.09	4.37	3.86	4.31	4.24	4.39
Greece	17444.38	2.84	3.17	3.30	3.06	3.18	3.66
Hungary	13869.73	3.35	3.27	3.22	3.21	3.67	3.79
Iceland	1150.68	2.77	3.19	2.79	3.61	3.35	3.70
Ireland	12202.06	3.36	3.29	3.42	3.60	3.62	3.76
Israel	18698.50	3.32	3.33	2.78	3.39	3.50	3.59
Italy	104276.16	3.47	3.85	3.51	3.66	3.85	4.13
Japan	204802.24	3.99	4.25	3.59	4.09	4.05	4.25
Kazakhstan	26150.75	2.66	2.55	2.73	2.58	2.78	3.53
Korea	98111.38	3.40	3.73	3.33	3.59	3.75	3.92
Latvia	3351.30	2.80	2.98	2.74	2.69	2.79	2.88
Lithuania	6077.07	2.85	2.73	2.79	2.96	3.12	3.65
Luxembourg	6027.14	3.53	3.63	3.37	3.76	3.61	3.90
Malta	671.39	2.70	2.90	2.70	2.80	2.80	3.01
Netherlands	31497.20	3.92	4.21	3.68	4.09	4.02	4.25
New Zealand	15126.26	3.71	3.99	3.43	4.02	3.92	4.26
Norway	13241.61	3.52	3.69	3.43	3.69	3.94	3.94

Poland	65150.96	3.25	3.21	3.68	3.58	3.51	3.95
Portugal	17256.61	3.17	3.25	3.83	3.71	3.72	4.13
Romania	18434.19	2.58	2.91	3.18	3.07	3.26	3.68
Russia	254077.22	2.42	2.78	2.64	2.75	2.65	3.31
Slovak Republic	7818.02	2.79	3.00	3.10	3.14	2.99	3.14
Slovenia	5841.65	3.42	3.26	3.19	3.05	3.27	3.70
Spain	90446.34	3.62	3.84	3.83	3.80	3.83	4.06
Sweden	17230.48	4.05	4.24	3.92	3.98	3.88	4.28
Switzerland	14925.51	3.63	4.02	3.51	3.97	4.10	4.24
Turkey	84616.68	2.71	3.21	3.06	3.05	3.23	3.63
Ukraine	34956.45	2.49	2.22	2.83	2.84	3.11	3.42
United Kingdom	122972.94	3.77	4.03	3.67	4.05	4.11	4.33
United States	1816671.44	3.78	4.05	3.51	3.87	4.09	4.08

The research algorithm of the study is presented in Figure 1. First of all, the research problem was determined. Following that, the literature background of the field was structured. The research sample data were collected from the databases. The data pre-processing was conducted. The dataset was normalized before analysis. Before clustering analysis, the tendency of clustering with the Hopkins statistic test was assessed. After that, the cluster numbers were determined with the Elbow method. Following that the Hierarchical K-means algorithm was applied to the normalized dataset with R language codes. In the next step, the countries were ranked by applying the EDAS method for each cluster. Finally, the results were interpreted.

Figure 1. Research Process



3.1. Hierarchical K-Means Clustering

Models in data mining can be divided into predictive and descriptive models (Han et al., 2006) In this research, the clustering analysis was applied which classified into descriptive models. Clustering analysis, which is frequently used in data mining, has become very popular because there is a lot of data accumulation today. Clustering analysis can be briefly mentioned as the process of separating data into clusters or classes in terms of similar characteristics. In the literature, there are many clustering methods such as hierarchical, density-based, partition-based, and artificial intelligence-based clustering (Jain et al, 1999; Berkhin, 2002; Kuo et al., 2005). Clustering analysis is a statistical technique aimed at classifying some objects into clusters according to their similarities (Suzuki & Shimodaira, 2006). Pvclust was designed for general hierarchical clustering complication. This allows researchers to easily obtain bootstrap p-values for their dataset and approved clustering method (Suzuki & Shimodaira, 2004).

If there is no output value in clustering methods, these inputs are grouped only according to their input values. Therefore, the purpose of clustering techniques is to discover groups of similar samples in the data (Balaban & Kartal, 2015) . Hierarchical clustering is a very advantageous and extensively used technique in data processing (Lu et al., 2008). For multiplex clustering involving large datasets and many dimensional attributes that are very difficult to visualize, hierarchical k-means can perform well in terms of both accuracy and agility (Arai & Ridho, 2007).

Clustering algorithms can be largely divided into two groups as hierarchical and divisive (Jain, 2010). Most hierarchical algorithms have quadratic or higher complexity in the number of data points and therefore are suitable for small datasets (Celebi et al., 2013). In the study, the clustering analysis is performed with the Hierarchical K-means algorithm by using the R program. The countries are divided into clusters in terms of their logistics performance and Transport-related CO_2 emission values. The Hierarchical K-means clustering has the skill to sense clusters of varying shapes and dimensions (Govender & Sivakumar, 2020). To conduct this, clustering analysis was performed using (factoextra) and (cluster) libraries of R. In R program the R function hkmeans() [in factoextra], provides a simple solution for computing hierarchical k-means clusters. The following steps were conducted for hierarchical clustering:

1st Step: Compute hierarchical clustering

2nd Step: Divide the tree into k clusters

3rd Step: Compute the center (mean) of each cluster.

4th Step: Run k-means using the set of cluster centers which was defiden in 3rd step as initial cluster centers. Optimize clustering. This causes the final optimized partitioning obtained in 4th Step to differ from that obtained in 2nd Step.

4. FINDINGS

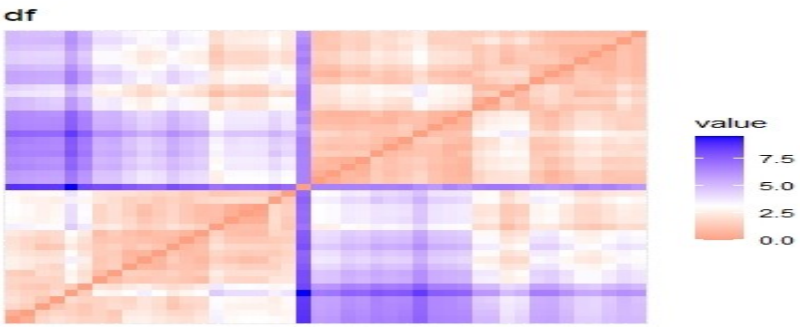
4.1. Assessing Clustering Tendency

For a given dataset, evaluating the clustering tendency evaluates whether the data has a non-random structure. Arbirtarily use of a clustering method to a dataset may hinder the accurate clusters. Clustering analysis of datasets is useful only when the data have a non-random structure.

In a research problem; the null hypothesis is the homogeneous hypothesis that D is uniformly distributed and thus contains no meaningful clusters. The nonhomogeneous hypothesis (i.e., that D is not uniformly distributed and thus contains clusters) is the alternative hypothesis. The Hopkins Statistic test can be conducted iteratively, using 0.5 as the threshold to reject the alternative hypothesis. That is, if $H > 0.5$, then it is unlikely that D has statistically significant clusters (Han et al., 2012).

In this research, the clustering tendency was measured by using the Hopkins statistic. As it is seen in Figure 2, the clustering tendency (VAT) analysis result shows that the dataset has a high tendency for clustering. According to the Hopkins statistic test result, the research data set is highly clusterable (the H value = 0.20 which is far below the threshold of 0.5). In addition to that, in order to visualize the research dataset as highly clusterable; the visual assessment of the cluster tendency approach was conducted.

Figure 2. The Visual Assessment of Cluster Tendency (VAT) Analysis Result

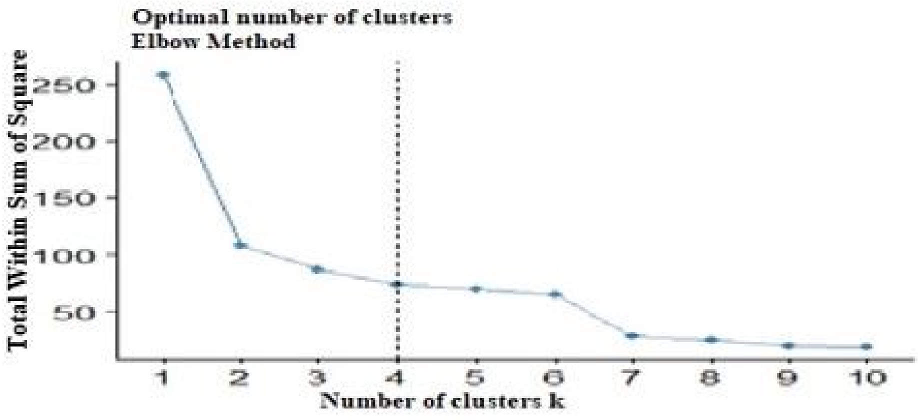


Red: high similarity (ie: low dissimilarity) | Blue: low similarity

4.2. Determining the Optimal Number of Clusters

In this study the value of k, that is, the number of clusters was systematically chosen by using the Elbow method. A technique known as the elbow method attempts to estimate how homogeneity or heterogeneity varies within a cluster for different values of k. This value of k is called the elbow dot because it looks like an elbow (Lantz, 2013). In this paper, the optimal number of cluster was found as 4 and presented in Figure 3.

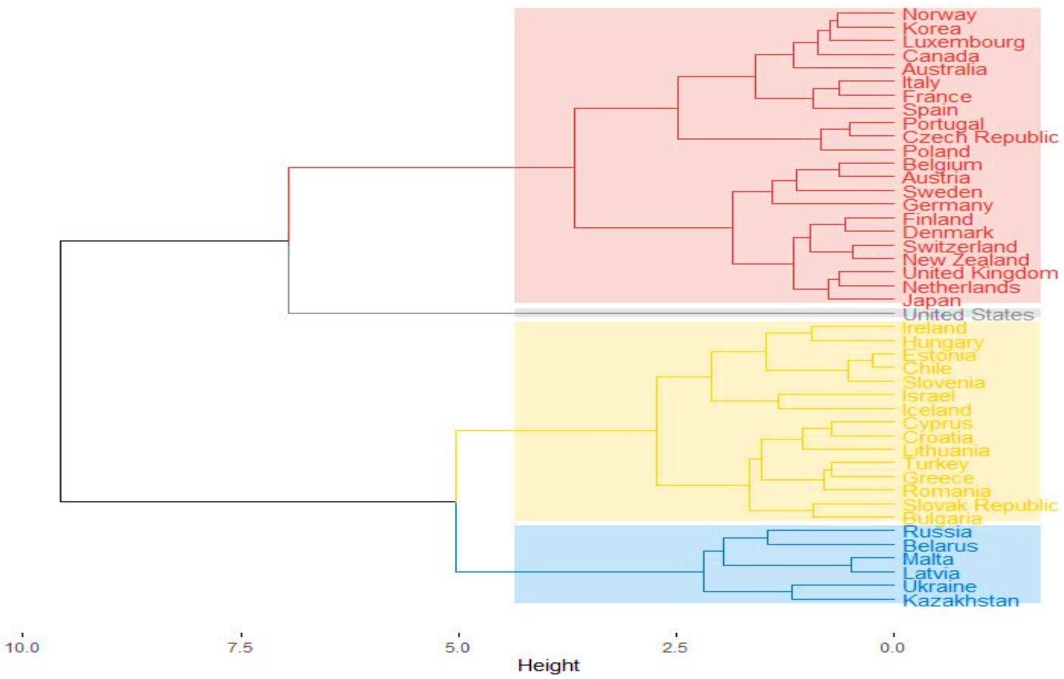
Figure 3. The Optimal Number of Cluster



4.3. Hierarchical K-Means Clustering Analysis Results

One of the advantages of hierarchical k-means clustering analysis is that it provides Dendrogram graphical representation (Govender & Sivakumar, 2020). A hierarchical method creates a hierarchical decomposition of the given set of data objects. A dendrogram is built due to the Tree of clusters. In clustering analysis, the results shown as tree diagrams are called dendograms (Sharma & Wadhawan, 2009). Every cluster node contains child clusters, and sibling cluster partition the points covered by their common parent.

Figure 4. Hierarchical K-means Cluster Dendrogram



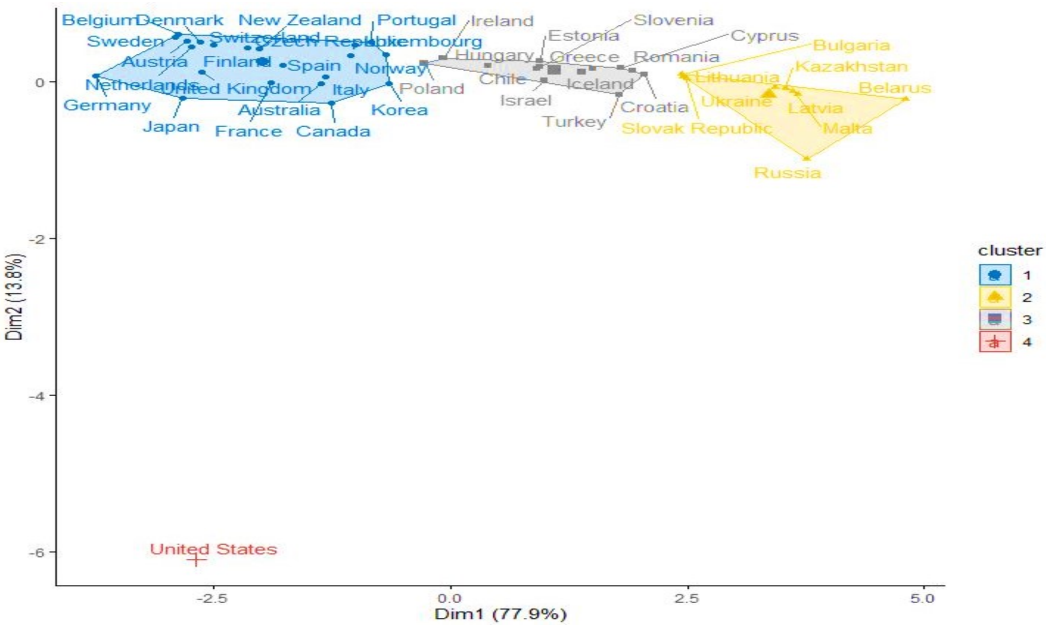
The hierarchical K-means cluster dendrogram is shown in Figure 4. According to the obtained dendrogram tree; the clusters in which the countries are classified are seen in four different colors blue, yellow, red, and gray.

According to the cluster dendrograms of Hierarchical K-means Russia, Belarus, Malta, Latvia, Ukraine, and Kazakhstan are divided into Blue Cluster. Following that, Iceland, Hungary, Estonia, Chile, Slovenia, Israel, Iceland, Cyprus, Croatia, Lithuania, Turkey, Greece, Romania, Slovak Republic, and Bulgaria was divided into Yellow Cluster which includes 15 countries. The United States is in Gray Cluster.

Finally, in the Red Cluster which includes 22 countries; Norway, Korea, Luxemburg, Canada, Australia, Italy, France, Spain, Portugal, Chech Republic, Poland, Belgium, Austria, Sweden, Germany, Finland, Denmark, Switzerland, New Zealand, United Kingdom, Netherlands, and Japan.

The Hierarchical K-means cluster plot is shown in Figure 5.

Figure 5. Hierarchical K-means Cluster Plot



The Hierarchical K-means cluster plot is shown in Figure 5. In order to better understand the clusters shown in the Hierarchical K-means cluster graph, they are presented in detail with the help of Table 3.

Table 3. Hierarchical K-means Clustering Results of Countries

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Australia	Belarus	Chile	United States
Austria	Bulgaria	Croatia	
Belgium	Kazakhstan	Cyprus	
Canada	Latvia	Estonia	
Czech Republic	Lithuania	Greece	
Denmark	Malta	Hungary	
Finland	Russia	Iceland	
France	Slovak Republic	Ireland	
Germany	Ukraine	Israel	
Italy		Poland	
Japan		Romania	
Korea		Slovenia	
Luxembourg		Turkey	
Netherlands			
New Zealand			
Norway			

Portugal Spain Sweden Switzerland United Kingdom			

The Hierarchical K-means clustering results of countries were presented in Table 3. When evaluated over the existing criteria, it has been understood that the countries in Cluster 4 and Cluster 1 are generally at the top of all criteria. United States was clustered in Cluster 4. The US has modern and developed transportation infrastructures. In addition to that United States is one of the giant economies globally. That means the transportation industry which is the most essential operating network of global trade, is developed. However, depending on the intensity of transportation, the amount of Greenhouse Gas Emissions from transportation is also extremely high.

According to the analysis results, besides the high logistics performance, it should consider its responsibilities towards the environment in transportation. At this point, the policymakers need to take strategic decisions to reduce transport-related CO_2 emissions. Countries in Cluster 1 such as Belgium, Germany, Japan, Spain, Netherlands, Norway, Denmark, Switzerland, United Kingdom, France, and Norway are the power representatives in the world's maritime trade. The countries in Cluster 1 are active in taking environmental steps and their implementation. In addition, the transportation infrastructures of the countries in this cluster are highly developed. However, Japan, Canada, Germany, France, United Kingdom, Italy, Australia, Korea, and Spain have active roles in international trade thus greenhouse gas emission rates increase caused by transportation. Therefore, it is strongly recommended to make environmentally friendly investments in transportation. Countries in Cluster 2 have low LPI values. However, especially since Russia is an important actor in world trade, the need to be active in transportation industry is quite high. Therefore, the amount of CO_2 emissions associated with transportation is high. In this case, it is vital for the countries in this cluster to improve their performance in the field of Logistics, while advancing with an environmentalist understanding. Turkey, which is an important representative in maritime transport, is in the 3rd Cluster. In Cluster 3 the countries have average scores in LPI. When we look at the other countries in the cluster, it is seen that they are among the developing economies. Turkey's high rate of transport-related CO_2 emissions from transportation supports sustainable developments in the logistics sector of environmentalist investments to be made in this field.

4.4. EDAS Method

In this study, the EDAS method was used to measure and rank the performance of clustered countries. The steps of the EDAS method can be summarized as follows (Özbek, 2021):

Step 1: *The initial matrix (X) is created.* Equation (1) shows the decision matrix. In this matrix xij; i option j. represents the performance according to the criteria.

$$X = [X_{ij}]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 2: *The average solution is determined according to all criteria.* This is done using equations (2) and (3).

$$AV_J = \frac{\sum_i^m \mathrm{x_{iJ}}}{m} \quad (2)$$

$$AV = [AV_j]_{1\mathrm{xn}} \quad (3)$$

Step 3: *Create a matrix of positive and negative distances from the mean.* For each criterion, a positive distance matrix (PDA) from the mean represented by Equation (4) and a negative distance matrix (NDA) from the mean by Equation (5) is formed. If the criterion is beneficial, the PDA and

NDA matrices are formed by Equations (6) and (7). If the criterion is non-beneficial, then the PDA and NDA matrices are calculated using Equations (8) and (9).

$$PDA = \left[PDA_{ij}\right]_{mxn} \quad (4)$$

$$NDA = \left[NDA_{ij}\right]_{mxn} \quad (5)$$

$$PDA_{ij} = \frac{max\left(0,(X_{ij}-AV_j)\right)}{AV_i} \quad (6)$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-X_{ij})\right)}{AV_i} \quad (7)$$

$$NDA_{ij} = \frac{max\left(0,(AV_j-X_{ij})\right)}{AV_i} \quad (8)$$

$$PDA_{ij} = \frac{max\left(0,(X_{ij}-AV_j)\right)}{AV_i} \quad (9)$$

Step 4: *Calculate the weighted sum of the options.* The weighted total PDA and NDA are calculated for each option. vj, j. shows the weights of the criteria.

$$SP_i = \sum_{j=1}^{n} v_j\, PDA_{ij} \quad (10)$$

$$PN_i = \sum_{j=1}^{n} v_j\, NDA_{ij} \quad (11)$$

Step 5: *Normalize the weighted sum of the options.* For each option, the SP and SN values are normalized using Equations (12) and (13).

$$NSP_i = \frac{SP_i}{max_i(SP_i)} \quad (12)$$

$$NSN_i = 1 - \frac{SN_i}{max_i(SN_i)} \quad (13)$$

Step 6: *Calculate the ranking score.* The evaluation score (AS) is calculated using Equation (14) for all options.

$$AS_i = \frac{1}{2}(NSP_i - NSN_i) \quad (14)$$

AS_i value must satisfy the $0 \leq AS_i \leq 1$ condition.

Step 7: *Sort all the options.* The options are sorted in descending order of AS score. The first option is considered the best. The AS_i scores obtained after the implementation of Step 7 are presented in table 4.

Tablo 4. AS Scores and Ranks of Countries

Cluster 1			Cluster 2			Cluster 3			Cluster 4	
Countries	AS_i	Rank	Countries	AS_i	Rank	Countries	AS_i	Rank	Country	
Sweden	0.996	1	Slovak Republic	0.997	1	Iceland	0.965	1	United States	1
Denmark	0.974	2	Lithuania	0.981	2	Estonia	0.954	2		
Finland	0.971	3	Bulgaria	0.957	3	Ireland	0.893	3		
Austria	0.918	4	Malta	0.923	4	Slovenia	0.890	4		
Belgium	0.910	5	Latvia	0.917	5	Cyprus	0.877	5		
Switzerland	0.904	6	Belarus	0.815	6	Hungary	0.780	6		
New Zealand	0.889	7	Kazakhstan	0.647	7	Croatia	0.772	7		
Netherlands	0.866	8	Ukraine	0.581	8	Israel	0.639	8		
Luxembourg	0.841	9	Russia	0.016	9	Greece	0.575	9		
Norway	0.816	10				Romania	0.514	10		
Portugal	0.776	11				Chile	0.496	11		
Czech Republic	0.775	12				Poland	0.393	12		
Spain	0.415	13				Turkey	0.008	13		
Germany	0.398	14								
United Kingdom	0.384	15								
Australia	0.354	16								
Italy	0.316	17								
Korea	0.291	18								
France	0.261	19								
Japan	0.122	20								
Canada	0.020	21								

Table 4 shows the EDAS method results. Each cluster was analyzed independently by applying the EDAS method. According to the AS scores and ranks of countries the best country among the countries in cluster 1 is Sweden. The country with the best AS score in the second cluster was the Slovak Republic. The country with the best performance in Cluster 3 is Iceland, while the country with the worst performance is Turkey. Since only United States is included in Cluster 4, no calculations were made on this cluster. Considering the AS_i scores of the countries belonging to the clusters in Table 4: the AS_i value of the best performing country for Cluster 1 was found to be 0.996. In addition, the AS_i value of Canada, which has the worst performance value, is 0.020.

Furthermore, the AS_i value of Slovak Republic which has the best performance value in Cluster 2, is 0.997. In addition to that, the AS_i value of Russia, which has the worst performance value, is 0.016. Moreover, the AS_i scores is 0.965 of Iceland which was ranked in first rank in Cluster 3. Turkey was ranked 13th in Cluster 3 as it has the worst AS_i performance value of 0.008.

Table 5. Ranking Results of the Countries in the Clusters according to the EDAS Method

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Sweden	Slovak Republic	Iceland	United States
Denmark	Lithuania	Estonia	
Finland	Bulgaria	Ireland	
Austria	Malta	Slovenia	
Belgium	Latvia	Cyprus	
Switzerland	Belarus	Hungary	
New Zealand	Kazakhstan	Croatia	
Netherlands	Ukraine	Israel	
Luxembourg	Russia	Greece	
Norway		Romania	
Portugal		Chile	
Czech Republic		Poland	
Spain		Turkey	
Germany			
United Kingdom			
Australia			
Italy			
Korea			
France			
Japan			
Canada			

Table 5 shows the ranking results of the countries in the clusters according to the EDAS method. According to Table 5, Cluster 1 includes 21 countries which are ranked from best to worst as Sweden, Denmark, Finland, Austria, Belgium, Switzerland, New Zealand, Netherlands, Luxembourg, Norway, Portugal, Czech Republic, Spain, Germany, United Kingdom, Australia, Italy, Korea, France, Japan, Canada, respectively. Cluster 1 typically includes countries performing well on LPI and transport-related carbon footprint.

Even though the railway network of Korea and Japan is developed, these countries are ranked last in Cluster 1. Cluster 2 includes 9 countries that are ranked from best to worst Slovak Republic, Lithuania, Bulgaria, Malta, Latvia, Belarus, Kazakhstan, Ukraine, and Russia, respectively. Cluster 3 includes 13 countries which are Iceland, Estonia, Ireland, Slovenia, Cyprus, Hungary, Croatia, Israel, Greece, Romania, Chile, Poland, Turkey, form best performed to worst, respectively. Since Turkey is an important actor both in terms of being a corridor in global trade and in exports, the transportation sector has developed. However, since Turkey has the lowest performance in cluster 3, it is understood that it needs to increase its initiatives to improve both its transport-related carbon footprint and logistics performance indicators. Turkey's 169.5 billion Dollar export was transported by sea with 59.6 percentage in 2021. Road mode is in the second place with 31.2%, and airway is in the third place with 7.5% (https://ticaret.gov.tr/). This can affect the transport-related CO_2 emissions as the road is the second most preferred mode of transportation, which is a fast mode of transportation. Cluster 4 includes only

United States. As it can clearly seen in Table 2, United States was with the highest transport-related CO_2 emission amount in the research dataset. United states is an economy with the second highest share in the global trade arena. According to the U.S. Department of Transportation, water transport was the dominant mode of transport for the 41.1 percent of the total value of all goods traded into and from the United States (U.S.) in 2021. Air transport was responsible for 29.6 percent of the value of all U.S. trade that year (www.bts.dot.gov). As it can be understood from this, the increase in the United States' attempts to use sea and rail transportation modes can reduce the level of carbon footprint. When all clusters are examined, it can clearly understand that the countries that have the high usage transportation industry or make wrong transportation modes decisions are listed in the last place.

5. CONCLUSION

The importance of transportation for the continuity of the global supply chain is undeniable. However, transportation is one of the leading sectors in terms of energy consumption and CO_2 emissions. For this reason, as a result of the more sustainable initiatives of this sector, there will be some improvement in the carbon footprint. Efforts made by countries to reduce emission values in these leading sectors in terms of preventing global climate change are vital. In this study, it is aimed to classify countries by considering their logistics performance and CO_2 emissions from transportation. For this purpose, 44 countries with CO_2 emissions from transportation are grouped in terms of their logistics performance according to 7 criteria. After performing the clustering algorithm, the EDAS method was applied to rank the logistics performances of the countries within each cluster. The purpose of this is to rank the countries in each cluster according to their logistics performance in the cluster they are in and to facilitate comparisons with other countries in the same cluster. Thus, it will make it easier for countries to make self-evaluations in improving their logistics activities in terms of environmental responsibility, according to the competitors in the cluster. Clusters will help countries take the necessary precautions regarding CO_2 emissions while performing their logistics activities.

In the first stage of the empirical study, hierarchical clustering analysis was performed using Customs, Infrastructure, International Shipments, Logistics Quality, Monitoring and Monitoring, Timeliness, and CO_2 emissions from transport data. According to the hierarchical clustering analysis, countries are divided into 4 clusters. Countries in Cluster 1 are generally seen to have good LPI scores and low carbon footprints. The fact that the United States is in a cluster alone indicates that the amount of CO_2 emissions from transportation is more dominant than other variables in the classification. To make an assessment for Cluster 2 and Cluster 3, developing countries are generally clustered in these clusters. In addition, these countries have lower LPI scores than Cluster 1. According to the EDAS method results: In Cluster 1 Sweeden has the best performance value, besides the country which has the worst performance was Canada. As it can be understood from here, Canada's carbon footprint is higher than Sweeden's. Sweeden has a sense of environmentally responsible transportation and its impact is easily felt here as it is lower than Canada in terms of population. Besides, Canada's foreign trade volume is more intense than Sweeden. This triggers the need for transportation. While Slovak Republic ranked in 1st rank, Russia ranked in 13th rank with the worst performance value in Cluster 2. In addition to that, in Cluster 3 Iceland has the best performance value and it ranked in 1st rank. However, Turkey ranked in the 13th rank in Cluster 3. Although Turkey is a peninsula country surrounded by the sea on three sides, it is one of the most preferred modes of transport for road transport and transportation rather than the use of railways and seaways due to various foreign trade costs. Recently, the invesments to railway infustructures are ingreasing day by day in Turkey. While most of the population prefers the road in their transportation preferences, railway mode usage remains at low levels. There is no doubt that every investment to be made in the railway will be steps with high environmental responsibility. Policimakers, investors, and other actors should support initiatives that will facilitate the choice of low-carbon transportation vehicles by changing the mode preferences in transportation. Furthermore, it is very important to support the environmental sustainability dimension of the logistics industry, which plays a key role in the global and national economy.

The study has some limitations regarding the data sample due to the fact that CO_2 equivalent greenhouse gas emission values are not shared by some countries. Additionally, the other limitation of this study was the Hierarchical k-means clustering algorithm, which is another limitation of this study, can be compared with different clustering analysis techniques in future studies.

This study will be a roadmap for researchers to propose a country that can carry out effective initiatives on sustainability in the logistics sector. In future studies, the results can be compared by increasing the number of countries and using different clustering techniques.

REFERENCES

1. ALYOUBI, B. A. (2021), "Clustering Analysis of Logistics Performance in Saudi Arabia: A Roadmap to Cloud Computing and IoT & Blockchain Solutions", International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies, 12(7), 12A7G, 1-14, http://TUENGR.COM/V12/12A7G.pdf DOI: 10.14456/ITJEMAST.2021.133.
2. ARAI, K. & RIDHO, A., "Hierarchical K-means: An Algorithm for Centroids Initialization for K-means".
3. ARVIS, J-F., OJALA, L., WIEDERER, C., SHEPHERD, B., RAJ. A., DAIRABAYEVA, K. & KILISKI, T. (2014), "Connecting to Compete 2018: Trade Logistics in the Global Economy: The Logistics Performance Index and Its Indicators", The World Bank, Communications Development Incorporated, Washington, DC, 2018.
4. BALABAN, E. M. & KARTAL, E. (2015), Veri Madenciliği ve Makine Öğrenmesi Temel Algoritmaları ve R Dili ile Uygulamaları, Çağlayan Publication, Istanbul.
5. BAYIR, T. & YILMAZ, Z. (2017), "Assesment of Logistic Performance Indexes of EU countries by AHP and VIKOR Methods", Middle East Journal of Education (MEJE), 3 (2), 73-92.
6. BERKHIN, P. (2002), "Survey of Clustering Data Mining Techniques", Accrue Software, Retrieved from http ://www. accrue, corn/ product s/researchpapers.
7. CELEBI, M. E., KINGRAVI, H. A. & VELA, P. A. (2013), "A Comparative Study of Efficient Initialization Methods for the K-means Clustering Algorithm", Expert Systems with Applications, 40(1), 200–210. https://doi.org/10.1016/j.eswa.2012.07.021.
8. DANACI, T. & NACAR, R. (2017), "Comparing the Foreign Trade and Logistic Performance of Turkey and EU Members with Cluster Analysis", PressAcademia: Procedia, 3(1): 31-36.
9. GOVENDER, P. & SIVAKUMAR, V. (2020), "Application of K-means and Hierarchical Clustering Techniques for Analysis of Air Pollution: A Review (1980–2019)", Atmospheric Pollution Research, 11(1), 40–56. https://doi.org/10.1016/j.apr.2019.09.009.
10. HAN, J., KAMBER, M., PEI, J. (2006), Data Mining, Southeast Asia Edition, Elsevier Science & Technology.
11. JAIN, A. K. (2010), "Data Clustering: 50 Years beyond K-means", Pattern Recognition Letters, 31(8), 651–666.
12. LI, Y., DU, Q., LU, X., WU, J. & HAN, X. (2019), "Relationship between the Development and CO_2 Emissions of Transport Sector in China", Transportation Research Part D: Transport and Environment, 74, 1–14. https://doi.org/10.1016/j.trd.2019.07.011.
13. LU, J. F., TANG, J. B., TANG, Z. M. & YANG, J. Y. (2008), "Hierarchical Initialization Approach for K-means Clustering", Pattern Recognition Letters, 29(6), 787–795.
14. MIKLAUTSCH, P. & WOSCHANK, M. (2022), "A Framework of Measures to Mitigate Greenhouse Gas Emissions in Freight Transport: Systematic Literature Review from a

Manufacturer's Perspective", Journal of Cleaner Production, 366, 132883. https://doi.org/10.1016/j.jclepro.2022.132883.

15. POLAT, M., KARA, K. & YALCIN, G. C. (2022), "Clustering Countries on Logistics Performance and Carbon Dioxide (CO_2) Emission Efficiency: An Empirical Analysis", Business and Economics Research Journal, 2. https://doi.org/10.20409/berj.2022.370.
16. Republic of Türkiye Ministry of Trade, "Republic of Türkiye Ministry of Trade 2021 Annual Report", Available from https://www.trade.gov.tr/, Accessed date: 28.11.2022.
17. RITCHIE, H., ROSER, M. & ROSADO, P. (2020), "$CO_2$and Greenhouse Gas Emissions", Our World in Data. Retrieved from https://ourworldindata.org/co2-emissions.
18. ROY, V., MITRA, S. K., CHATTOPADHYAY, M., SAHAY, B. S. (2018), "Facilitating the Extraction of Extended Insights on Logistics Performance from the Logistics Performance Index Dataset: A Two-stage Methodological Framework and its Application", Research in Transportation Business & Management, 28, 23-32.
19. SCHIPPER, L. (2009), "Fuel Economy, Vehicle Use and Other Factors Affecting CO_2 Emissions from Transport", Energy Policy, 37 (10), 3711e3713.
20. SENIR, G. (2021), "Comparison of Domestic Logistics Performances of Turkey And European Union Countries in 2018 with an Integrated Model", LogForum 17(2), 193-204, http://doi.org/10.17270/J.LOG.2021.576.
21. SUZUKI, R. & SHIMODAIRA, H. (2006), "Pvclust: An R Package for Assessing the Uncertainty in Hierarchical Clustering", Bioinformatics, 22(12), 1540–1542. https://doi.org/10.1093/bioinformatics/btl117.
22. TRAPPEY, C. V., TRAPPEY, A. J., CHANG, A. C. & HUANG, A. Y. (2010), "Clustering Analysis Prioritization of Automobile Logistics Services", Industrial, Management & Data Systems, 110 (5): 731-743.
23. ULUTAŞ, A. & KARAKÖY, Ç. (2019), "G- 20 Ülkelerinin Lojistik Performans Endeksinin Çok Kriterli Karar Verme Modeli ile Ölçümü", Journal of Economics and Administrative Sciences, 20 (2): 71-84.
24. U.S. Department of Transportation, (2022), "Transportation Statistics Annual Report", Available from 2021//www.bts.dot.gov/sites/bts.dot.gov/files/2022-01/TSAR_FULL%20BOOK-12-31-2021.pdf, Accessed date: 15.12.2022.
25. YANG, W., LI, T. & CAO, X. (2015), "Examining the Impacts of Socio-economic Factors, Urban Form and Transportation Development on CO_2 Emissions from Transportation in China: A Panel Data Analysis of China's Provinces", Habitat International, 49, 212-220.
26. YILDIZ, A., AYDOĞAN, K. & KARTUM, G. (2020), "Türkiye'nin Uluslararası Lojistik Performans Endeksindeki Konumunun Kümeleme Analizi ile Araştırılması", Turkish Studies-Social, 15 (3): 1659-1679.